Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 3278239, 13 pages
https://doi.org/10.1155/2022/3278239

Research Article

Research on Operation and Maintenance Route Planning of Offshore Wind Farm Based on Multiagent

Mei Yu,[1] Yuyang Sheng,[1] Hang Sun ,[1] Yuelin Zheng,[1] Hongyang Li,[2] and Wen Yang[3]

[1]*Hubei Engineering Technology Research Center for Farmland Environmental Monitoring, Three Gorges University, Yichang 443002, China*
[2]*Hubei Province Engineering Technology Research Center for Construction Quality Testing Equipments, Three Gorges University, Yichang 443002, China*
[3]*Hubei Key Laboratory of Intelligent Vision Based Monitoring for Hydroelectric Engineering, Three Gorges University, Yichang 443002, China*

Correspondence should be addressed to Hang Sun; sunhang0418@whu.edu.cn

Received 22 July 2022; Revised 6 September 2022; Accepted 16 September 2022; Published 12 October 2022

Academic Editor: Jian Feng Li

Recently, the ant colony algorithm has been widely used in the field of path planning, which is a key technology required for ship operations in offshore wind farms to improve navigation efficiency and power generation. However, the ant colony algorithm has the defects of a long search time and stagnation in the early stage of the operation and maintenance path planning of offshore wind farms, and it easily falls into the problem of local optima; furthermore, the ant colony algorithm uses incremental construction to build a complete itinerary path, it takes a lot of time to search the path, and only the suboptimal solution is obtained. To address the above problems, in this paper, we propose a multi-agent-based operation and maintenance model for offshore wind farms. Specifically, the introduction of the heuristic factor can optimize the local optimal solution and make the ant colony algorithm clearer when searching for the target. Based on this, increasing the pheromone adjustment factor can eliminate the invalid path from searching and select a high-quality path. In addition, by integrating the genetic algorithm, it is possible to select, cross, and mutate to simulate the natural evolution process to search for the optimal solution, reduce the similarity of the paths constructed by the ant colony, reduce the probability of algorithm stagnation, improve the convergence speed, and improve the time efficiency and solution accuracy of the algorithm. Simulation experiments on a series of benchmark datasets show that the proposed GA-PACO algorithm achieves better performance in global search and path planning than the existing three algorithms.

1. Introduction

Recently, China's offshore wind power is in the stage of large-scale development. Compared with developed countries in Europe, although China's offshore wind power started late, it is gradually becoming the main development direction of wind power in the eastern coastal areas of China and the commanding height of wind power technology to be climbed in the future. By the end of 2021, the cumulative installed capacity of wind power in China had reached 330 million kW, an increase of 16.6%, including 300 million kW of onshore wind power and 26.39 million kW of offshore wind power. With the gradual expansion of the construction scale of offshore wind farms, the operation and maintenance of offshore wind farms have gradually put forward higher requirements. Therefore, in order to improve the power generation of offshore wind power, it is of economic value and practical significance to optimize the operation and maintenance path of offshore wind turbines, reduce the waiting time for wind turbine maintenance, and reduce the maintenance cost.

Path planning technology has become a topic of research widely used in various fields and has high research value. The main core of path planning technology lies in the path planning algorithm. According to the path planning algorithm, the search of the optimal path is realized, and the obtained route is the barrier-free safe path between the starting point and the target point. Path planning algorithms are mainly divided into traditional algorithms and intelligent bionic algorithms. Traditional algorithms include Dijkstra algorithm and A^* algorithm. Intelligent bionic algorithms include ant colony algorithm [1–5], genetic algorithm [6–9], and simulated annealing algorithm. From the development of traditional algorithm and intelligent bionic algorithm to their combination, it reflects the development of path planning technology.

The ant colony algorithm and genetic algorithm have made great progress in the fields of vehicle transportation [10, 11], ship transportation [12], robots [13], UAV [14], and so on. This paper introduces the application of the ant colony algorithm and genetic algorithm in the field of path planning applications. Hu et al. [15] used the head-tail search mechanism and genetic algorithm to optimize the parameters of the improved ant colony algorithm and introduced reward and punishment factors and multi-index fitness functions, which greatly improved the avoidance of local optimization and the convergence speed; Jing et al. [16] improved the global search ability by improving the heuristic function and pheromone volatility factor, which can better improve the algorithm convergence speed, but the improvement of path smoothness is not enough. Kuczkowski and Śmierzchalski [17] innovatively proposed single-population and multipopulation genetic algorithms, introduced ship navigation-related constraints, and realized ship obstacle avoidance path planning. Genetic algorithms have made great progress in rescue robots, automatic navigation vehicles, mobile robots, express vehicles, etc., while the global search power is strong and can effectively deal with complex optimal solution problems.

However, the key issues that need to be addressed are (1) the ant colony algorithm has a long search time in the early stage, and it easily falls into the local optimum; (2) How to improve the volatilization rate of pheromones correctly and avoid excessive concentration of pheromones. It makes it more possible for ants to explore the potential optimal path and improves the global search ability of the algorithm..

In this paper, we propose a multi-agent-based offshore wind farm operation and maintenance model by integrating a genetic algorithm and an ant colony algorithm that introduces a heuristic factor and a pheromone adjustment factor, which improves the time efficiency and solution accuracy of the algorithm. Specifically, the heuristic factor is modified by calculating the transition probability of each node; the pheromone is dynamically updated, etc. to improve the ant colony algorithm; and the overall search ability of the ant colony is improved, so that the search path is optimal. Based on this, through the update of pheromones, the strategy and the adjustment of the volatility coefficient of the pheromone make the ant colony search path more purposeful and the global search ability is improved; in addition, by optimizing the update strategy of pheromones and combining it with a genetic algorithm, the local search ability is improved through nonlinear reinforcement search.

The main contributions of this work are summarized as follows:

(1) We propose a multi-agent-based operation and maintenance model for offshore wind farms and introduce a heuristic factor to incorporate the distance between the next node and the last node into the heuristic information function, so as to solve the problem that the current node and the same target node are connected, and the central node forms a local search interval

(2) With the influence of pheromone adjustment factor on the performance of the algorithm, the pheromone of the optimal path and the pheromone of the poor path are introduced to improve it, so as to help the ants find the shortest path during the search, thereby improving the performance of the pheromone algorithm

(3) The fusion genetic algorithm, with its advantages in global search and function optimization, reduces the probability of algorithm stagnation and improves the convergence speed. Our algorithm shows good performance on a series of benchmark datasets

The rest of this article is organized as follows. Section 2 provides an overview of related work. Section 3 presents the algorithm of GA-PACO. In Section 4, simulation experiments on a series of benchmark datasets are conducted to verify the effectiveness of the proposed method. Finally, Section 5 concludes the paper.

2. Related Work

2.1. Ant Colony Algorithm. The ant colony algorithm is a simulation optimization algorithm that simulates the foraging behavior of ants. It was first proposed by Italian scholar Dorigo M et al. in 1991 and was first used to solve TSP (Traveling Salesman Problem). Ants release pheromones on the path. When they encounter an intersection that has not yet been passed, they randomly choose a road to walk. At the same time, they release pheromones related to the length of the path. The concentration of pheromones is inversely proportional to the length of the path. Then, when the ants encounter the intersection again, they choose the path with the higher pheromone concentration. When the pheromone concentration on the optimal path increases, the ant colony finds the optimal foraging path. The traditional ant colony algorithm has excellent search performance, but there are still problems such as easily falling into a local optimum and a slow convergence speed.

Due to these shortcomings, a series of improved ant colony algorithms have been proposed in recent years. Liu and others [18] proposed a heterogeneous multi-ant colony strategy, which can balance the convergence and diversity of the algorithm and help the ant colony to jump out of the local optimal solution; nevertheless, when the global optimal solution is found, it takes a long time to play the role of positive feedback. Wang and Han [19] search the adaptive optimization parameters using hybrid symbiotic organisms and introduced a local optimization strategy to improve the convergence speed of the algorithm. If the initial parameters are not properly selected, the optimization ability of the algorithm will be weakened. Li et al. [20] proposed an ant colony optimization algorithm for the adaptive greedy strategy to optimize the path problem, but the algorithm is easy to fall into local optimization. Allal et al. [21] adopted the weather and resource-based ant colony algorithm to optimize the routing, maintenance, and scheduling of wind farms, which can effectively speed up the convergence speed compared with the traditional algorithm; however, in the case of insufficient iterations, it is still easy to appear local optimal solutions, and the global optimal solution cannot be obtained.

2.2. Offshore Wind Farm Path Planning. Nowadays, the operation and maintenance [22–25] of offshore wind farms have become a problem that needs to be solved very much, and the great increase in the difficulty of operation and maintenance has also caused great research difficulties to current researchers.

The path planning problem is usually summarized as the vehicle routing problem (VRP). The commonly used algorithms in VRP are the ant colony algorithm and genetic algorithm, etc., which mainly pursue high solution efficiency and strong practicability. Nielsen and Sorensen [26] took the lowest cost of operation and maintenance scheduling of offshore wind farms as the optimization goal and solved the operation and maintenance queue problem based on two improved memory genetic algorithms.

Offshore wind power operation and maintenance path planning should also consider solutions for multiple operation and maintenance ships. For example, Kou et al. [27] proposed the multistation vehicle routing problem (MDVRP), and Papadopoulos et al. [28, 29] used different clustering methods to decompose the MDVRP into multiple single-distributed center VRPs to solve. Neshat et al. [30] consider the multiagent path planning (MAPP) problem as a problem of finding a set of optimal paths for multiple agents from a starting position to a target position without conflict. Considering the availability of technicians, ships, and spare parts, Theuer et al. [31] proposed an optimization model for wind farm operation and maintenance scheduling with multiple ships, multiple maintenance days, and multiple locations.

The operating state of wind turbines in large-scale offshore wind farms is random and different, which has a certain impact on the decision-making of wind farm maintenance. In the operation and maintenance path planning, Zhu et al. [32] considered the constraints of time windows. The operation and maintenance of offshore wind power are easily restricted by the weather conditions at sea, and it is difficult to supply ships at sea. It is necessary to complete the operation and maintenance tasks as quickly as possible within the time window.

3. Method

3.1. Problem Description. The problem is described as follows: the terminal has prepared a certain number of operation and maintenance ships; the maximum ship transportation capacity and the coordinates of the terminal position are known; the coordinates of the wind turbines that need to be operated and maintained are known, and the expected time required for the operation and maintenance is known according to historical statistics. The goal is to minimize total power generation through optimal ship path planning. To facilitate analysis and research, the following assumptions are made:

(1) All ships are of the same type

(2) When each wind turbine is shut down, only one operation and maintenance ship is accepted for its service

(3) Each ship departs from the same pier and eventually returns to the original pier

(4) The coordinates of the wind turbines are fixed; the distance between the wind turbines can be calculated

(5) When each wind turbine fails, the required repair or maintenance time can be estimated (based on historical data)

(6) Each ship goes out to sea for maintenance once, which needs to be constrained by the time window

3.2. Constraints. The number of ships to be repaired and the maintenance sequence of units need to meet the following conditions:

$$\sum_{j=0}^{n} x_{0j}^{k} \leq 1, \quad k = 1, 2, \cdots, m, \tag{1}$$

$$\left(t_i^k + T_i + t_{ij} - t_j^k\right) x_{ij}^k \leq 0, \quad i, j = 1, 2, \cdots, n, k = 1, 2, \cdots, m, \tag{2}$$

$$t_{n+1}^{k} \leq T_{\max}, \tag{3}$$

$$y_i, z_i \geq 0, \quad i = 1, \cdots, n, \tag{4}$$

$$\sum_{i=1}^{n} \sum_{k=1}^{m} x_{ij}^{k} = 1, \quad j = 1, 2, \cdots, n, \tag{5}$$

$$\begin{aligned} \sum_{j=1}^{n} x_{0j}^{k} &= 1, \\ \sum_{i=1}^{n} x_{i0}^{k} &= 1. \end{aligned} \tag{6}$$

(1) The maximum number of ships to be repaired is as in equation (1), and the number of ships to be repaired at sea cannot exceed the total number of ships

(2) The maintenance time of crew j is after its end time and travel time. The maintenance sequence of the

crew is as shown in equation (2), where t_{id}^k is the time when ship k arrives at crew i on the d day and T_i is the stay time of the ship at crew i, including the time for personnel to pick up and maintain the unit; t_{ij} is the time from unit i to unit j

(3) The daily effective working time limit of the maintenance ship is as in equation (3), where t_{n+1}^k is the time when the ship k returns to the port after performing maintenance, $T_{\max}$ is the longest working time of the ship per day

(4) Maintenance shutdown and delayed maintenance time need to satisfy equation (4)

(5) Each unit is maintained by only one maintenance ship per day, and the number of daily maintenance units on the ship needs to satisfy the equation (5)

(6) The maintenance route needs to satisfy the equation (6)

3.3. Algorithmic Model Framework. We propose a multi-agent-based path planning operation and maintenance model, using K-means clustering algorithm to extract turbine features, and the result partition of genetic algorithm, as the global search and function optimization of the initial pheromone algorithm of the ant colony. Secondly, the heuristic information function of the traditional ant colony algorithm is improved. The local optimal solution is optimized to make the ant colony algorithm clearer, and the convergence speed is faster; then, the pheromone adjustment factor is introduced to improve the performance of the pheromone algorithm, select high-quality paths, and reduce stable iterations; finally, the two algorithms are fused, namely, the GA-PACO algorithm process is shown in Figure 1.

The GA-PACO algorithm steps are as follows.

Step 1. Initial partitioning of wind turbines based on the operating state of wind turbines.

Step 2. Partition clustering of wind turbine groups based on wind turbine status.

Step 3. Select a set of turbine groups to be selected for maintenance.

Step 4. Initialize the parameters and chromosomes of the genetic algorithm; retain the global optimum at the current moment.

Step 5. Perform selection, crossover, and mutation operations; update the global optimum.

Step 6. When the optimal individual converges or reaches the maximum number of iterations, the termination condition is met, and the suboptimal solution is output.

Step 7. Calculate the position to be reached by the ants in the next step according to the improved state transition probability formula.

Step 8. Update the pheromones of the ant colony algorithm according to the optimal path; initialize the parameters of the ant colony algorithm.

Step 9. Calculate the ant path length; update the pheromone.

Step 10. When the optimal individual converges or reaches the maximum number of iterations, the termination conditions are met, and the optimal solution is output.

3.4. GA-PACO Algorithm. The GA-PACO algorithm we proposed combines genetic algorithm and ant colony algorithm and introduces heuristic factors and pheromone adjustment factors. The details are as follows: firstly, genetic algorithm is used for fast selection, which lays a foundation for subsequent feature extraction. Update the pheromone allocation of the ant colony algorithm, use the positive feedback mechanism of the ant colony algorithm to replace some individuals of the genetic algorithm through the iteration of the ant colony algorithm, accelerate the iteration speed of the genetic algorithm, and realize the local optimal solution. The two algorithms are fused many times, and the global optimal path is obtained by crossing the local optimal solution.

3.4.1. Introducing Heuristics. The heuristic value $\eta_{ij}(t)$ of the traditional ant colony algorithm is only obtained by the reciprocal of the distance between the two nodes before and after, which cannot reflect the connection between the current node and the same target node; however, through the central node, the local search interval is formed, and only the local search can be obtained. To solve the above problems, the heuristic factor is now introduced, and the distance between the next node j and the final node z is incorporated into the heuristic information function, and the improvement after the introduction of the heuristic factor is defined in the following equation:

$$\left[\eta_{ij}(t)\right]^{-1} = \gamma_{ij}(t) + \gamma_{jz}(t), \tag{7}$$

where γ_{ij} represents the distance between node i and the next node j at time t and γ_{jz} represents the distance between the next node j and the final node z at time t. After integration γ_{jz}, the ant colony algorithm can make the search target more clearly and can improve the convergence speed of the ant colony algorithm. That is, the improved transition probability is defined in the following equation:

$$P_{ij}^k(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\gamma_{ij}(t) + \gamma_{jz}(t)\right]^{-\beta}}{\sum_{s\in N_i^k}\left[\tau_{is}(t)\right]^{\alpha}\left[\gamma_{is}(t) + \gamma_{sz}(t)\right]^{-\beta}}, j \in N_i^k \\ 0, j \notin N_i^k \end{cases} \tag{8}$$

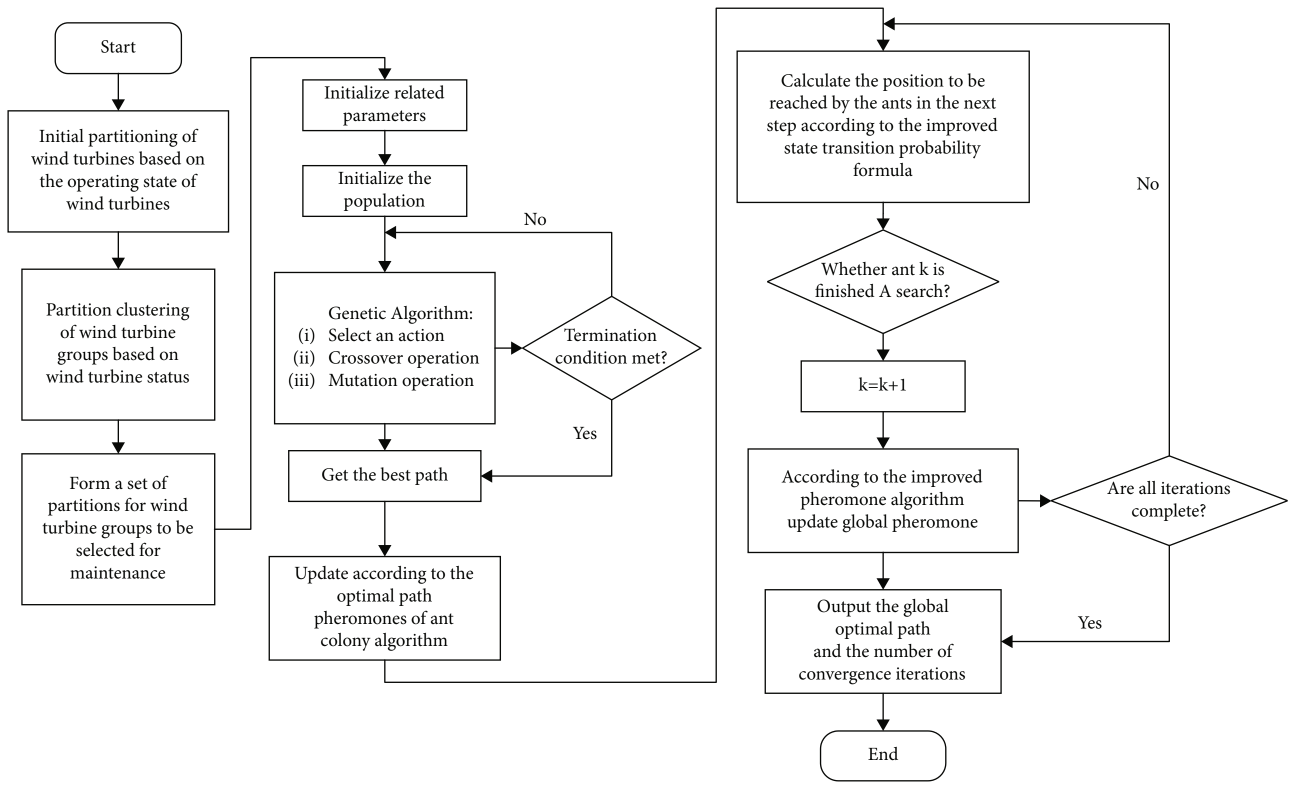

Figure 1: GA-PACO algorithm flow.

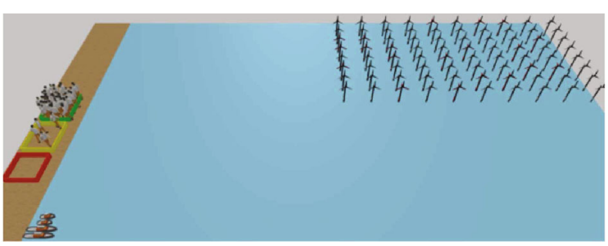

Figure 2: 3D turbine position and status.

where i denotes the current node; j denotes the next node; N_i^k denotes the node that the ant has not selected, namely, the next optional turbines set; and $\tau_{ij}(t)$ and $\eta_{ij}(t)$ denote the pheromone concentration and heuristic value at time t, respectively.

3.4.2. Improve the Performance of Pheromone Algorithm. In the traditional ant colony algorithm, the pheromone volatility factor ρ has a great influence on the performance of the algorithm, and only the same pheromone volatility factor ρ is used on the optimal path and the poor path. When ρ is small, there will be a small difference in pheromone concentration between the optimal path and the poor path; when ρ is large, the pheromone volatilization speed between the two will be accelerated, and the difference in pheromone concentration will become larger, and it is easy to stuck in a local optimum. In order to improve the quality of the local optimal value, this paper will introduce the pheromone of the optimal path and the pheromone of the poor path to help the ants find the shortest path when searching, so as to improve the performance of the pheromone algorithm. That is, the improved pheromone is defined in equations (9), (10), and (11):

$$\tau_{ij}(t+n) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij}(t) + \Delta\tau_{ij}^{b}(t) - \Delta\tau_{ij}^{w}(t), \tag{9}$$

$$\Delta\tau_{ij}^{b}(t) = \begin{cases} \partial\omega\sqrt{(L_b(t) - L_w(t))^2}, & i \in \mathrm{Ub}, j \in \mathrm{Ub}, \\ 0, \quad i \notin \mathrm{Ub}, j \notin \mathrm{Ub}, \end{cases} \tag{10}$$

$$\Delta\tau_{ij}^{w}(t) = \begin{cases} \theta\omega\sqrt{(L_b(t) - L_w(t))^2}, & i \in \mathrm{Uw}, j \in \mathrm{Uw}, \\ 0, \quad i \notin \mathrm{Uw}, j \notin \mathrm{Uw}, \end{cases} \tag{11}$$

where $\Delta\tau_{ij}^{b}(t)$ and $\Delta\tau_{ij}^{b}(t)$, respectively, represent the pheromone increment of the optimal path and the pheromone decrement of the poor path at time t; ∂ and θ, respectively, represent the optimal number and the poor number of ants in this iteration; ω represents the pheromone adjustment factor; $L_b(t)$ and $L_a(t)$, respectively, represent the optimal path length and the poor path length in this iteration; and Ub and Uw represent the set of the optimal path and the poor path, respectively.

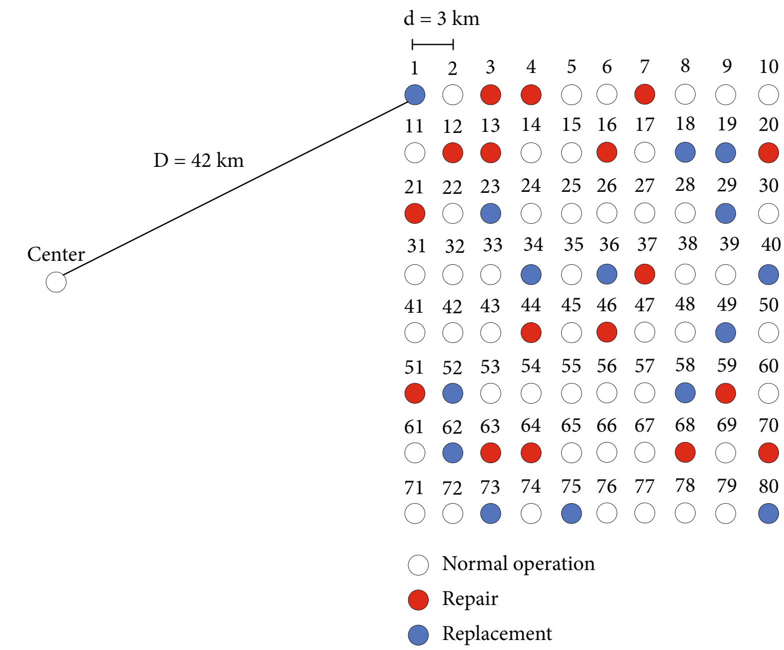

Figure 3: 2D turbine position and status.

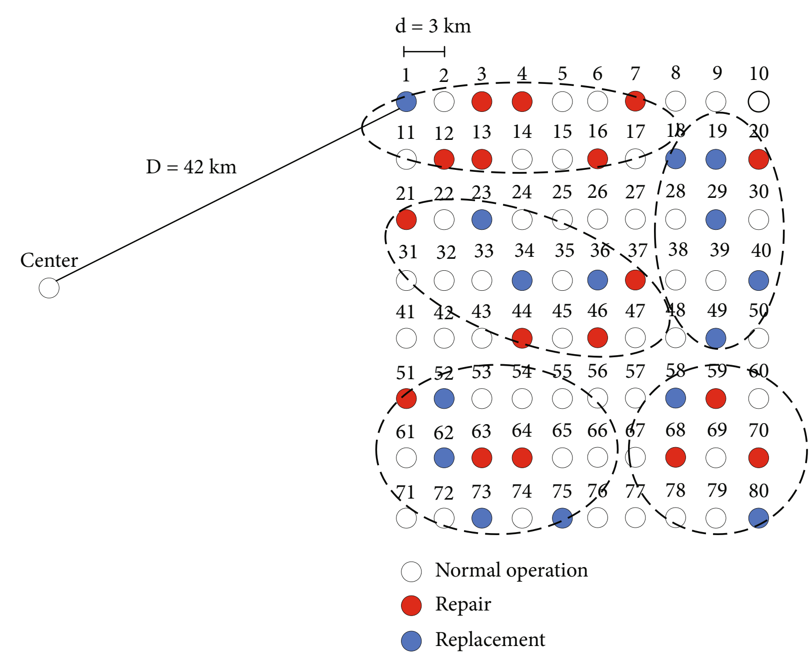

Figure 4: Turbine cluster partition.

3.4.3. Fusion Genetic Algorithm. The traditional genetic algorithm has advantages in global search and function optimization and is suitable for solving discrete multivariable and multiobjective nonlinear optimization problems. The initial search speed is fast, and the natural evolution process is simulated by selection, crossover, and mutation to search for optimal solutions, reducing ant colonies. The similarity of the constructed paths reduces the probability of algorithm stagnation, improves the convergence speed, and improves the time efficiency and solution accuracy of the algorithm. The basic process of the genetic algorithm is as follows.

Step 1. Select the best individual.

Firstly, the optimal individual is selected by roulette, the probability of being selected is defined in the following

Table 1: Average maintenance time for offshore wind turbines.

Turbine	x	y	Average maintenance time (h)	Turbine	x	y	Average maintenance time (h)
T1	118.488	24.493	2	T40	118.515	24.512	2
T3	118.494	24.497	5	T44	118.497	24.5	5
T4	118.497	24.5	5	T46	118.503	24.506	5
T7	118.506	24.509	5	T49	118.512	24.493	2
T12	118.491	24.5	5	T51	118.488	24.497	5
T13	118.494	24.503	5	T52	118.491	24.5	2
T16	118.503	24.512	5	T58	118.509	24.496	2
T18	118.509	24.496	2	T59	118.512	24.497	5
T19	118.512	24.497	2	T62	118.491	24.506	2
T20	118.515	24.5	5	T63	118.494	24.509	5
T21	118.488	24.503	5	T64	118.497	24.512	5
T23	118.494	24.509	2	T68	118.509	24.5	5
T29	118.512	24.503	2	T70	118.515	24.506	5
T34	118.497	24.496	2	T73	118.494	24.493	2
T36	118.503	24.5	2	T75	118.5	24.497	2
T37	118.506	24.503	5	T80	118.515	24.512	2

Table 2: Comparison of operation and maintenance strategies.

Area	Algorithm	Path	Power generation (kWh)
Area 1	GA-PACO algorithm	Center-T1-T3-T4-T7-T16-T13-T12	99590
	Fixed strategy	Center-T1-T12-T13-T3-T4-T16-T7	91252.5
	Ant colony algorithm	Center-T1-T3-T12-T13-T4-T7-T16	98325
	Genetic algorithm	Center-T1-T12-T13-T3-T4-T16-T17	91252.5
Area 2	GA-PACO algorithm	Center-T21-T23-T34-T36-T37-T46-T44	84927.5
	Fixed strategy	Center-T21-T23-T34-T44-T46-T36-T37	74290
	Ant colony algorithm	Center-T21-T23-T34-T44-T36-T46-T37	79350
	Genetic algorithm	Center-T21-T23-T34-T44-T46-T36-T37	74290
Area 3	GA-PACO algorithm	Center-T18-T19-T29-T49-T30-T20	49565
	Fixed strategy	Center-T18-T19-T20-T30-T29-T49	41400
	Ant colony algorithm	Center-T18-T19-T29-T20-T30-T49	45482.5
	Genetic algorithm	Center-T49-T30-T20-T29-T19-T18	43010
Area 4	GA-PACO algorithm	Center-T51-T52-T62-T73-T63-T75-T64	73082.5
	Fixed strategy	Center-T51-T52-T62-T63-T73-T64-T75	64112.5
	Ant colony algorithm	Center-T51-T52-T62-T73-T75-T64-T63	72220
	Genetic algorithm	Center-T51-T52-T62-T63-T64-T75-T73	66177.5
Area 5	GA-PACO algorithm	Center-T58-T80-T70-T59-T68	42032.5
	Fixed strategy	Center-T58-T68-T59-T70-T80	34212.5
	Ant colony algorithm	Center-T58-T59-T70-T80-T68	39790
	Genetic algorithm	Center-T58-T59-T68-T70-T80	36110

equation:

$$P(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)}, \tag{12}$$

where $f(x_i)$ represents the fitness value of the individual.

Step 2. Partial gene fragment cross in chromosome.

Crossover is the process of recombination of the better fragments in chromosomes to form new individuals, which is defined in equations (13) and (14).

$$\bar{m}_{kj} = m_{kj}(1-n) + m_{lj}n, \tag{13}$$

$$\bar{m}_{lj} = m_{lj}(1-n) + m_{kj}n, \tag{14}$$

where m_{kj} and m_{lj} denote the value of the j gene on

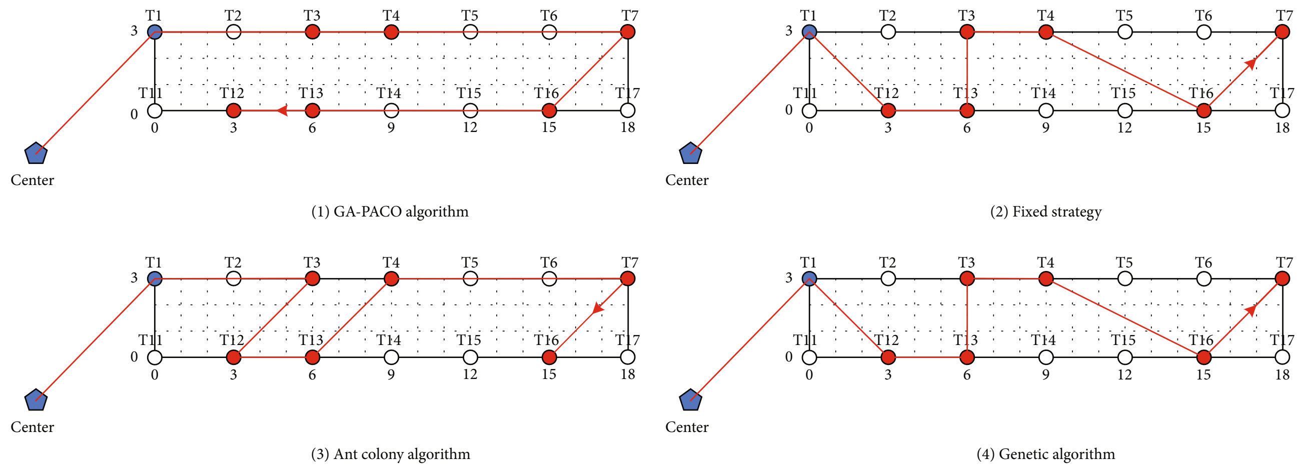

Figure 5: Area 1.

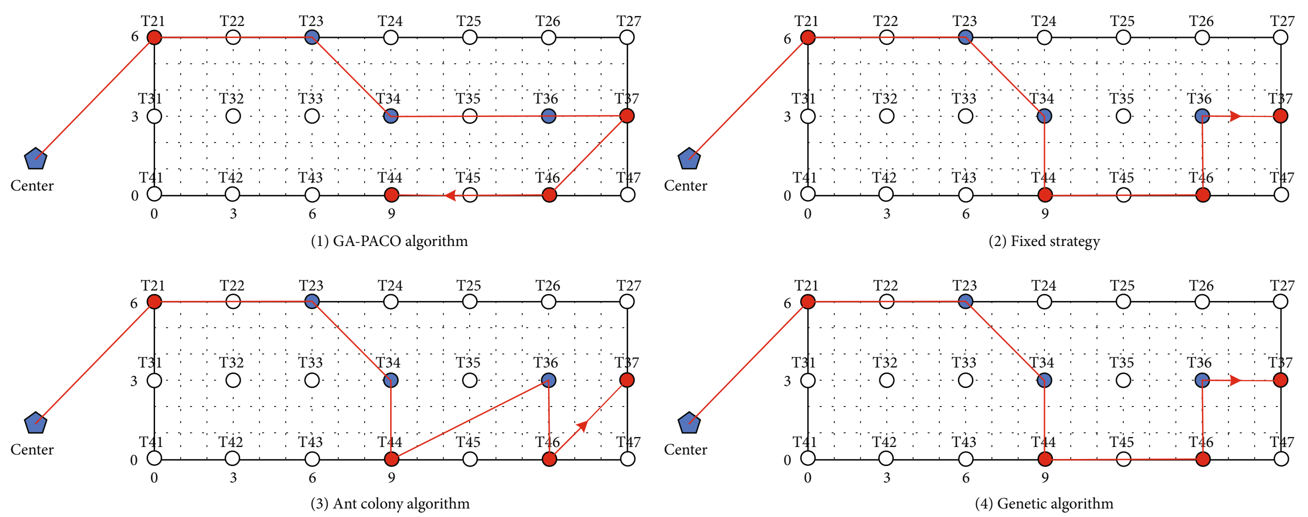

Figure 6: Area 2.

chromosomes k and l, respectively, and n denotes the random number $n \in [0, 1]$.

Step 3. Adaptive variation.

The mutation operation can reflect the local search ability of the genetic algorithm and obtain the local optimal solution; that is, the process of adaptive mutation is defined in the following equation:

$$P_m = \begin{cases} \dfrac{P_{m\,\max} - P_{m\,\min}}{1 + \exp\left(A\left(\left(f - \bar{f}\right)/\left(f_{\max} - \bar{f}\right)\right)\right)} + P_{m\,\min}\left(f \geq \bar{f}\right), \\ P_{m\,\max}\left(f < \bar{f}\right), \end{cases} \quad (15)$$

where $P_{m\,\max}$ and $P_{m\,\min}$ represent the maximum and minimum mutation probability, $f_{\max}$ represents the maximum fitness value of the population, and $\bar{f}$ represents the average fitness value of the population.

4. Experiments and Result Analysis

4.1. Experimental Setting. For the realistic simulation of the operation and maintenance path of offshore wind farms, these attempts may lead to huge costs and waste of resources. In response to this problem, we developed a simulation platform for turbine operation and maintenance paths to ensure safe and effective learning. In particular, virtual simulation experiments were performed using AnyLogic simulation software on a Windows Intel(R) Core (TM) i5-10500 CPU @ 3.10 GHz operating system. The dataset of wind speed, wave height, and multiagent comes from a wind farm in Jiangsu, and the proposed problems and evaluation indicators are implemented in the simulation environment. The validity of the model is fully verified by 80 wind turbines and 160 wind turbines.

4.2. Evaluation Metrics. There are many existing operation and maintenance ships for maintenance and repair, regardless of the influence of wind speed and wave height on the ship speed, and the ship travels in a straight line; the power

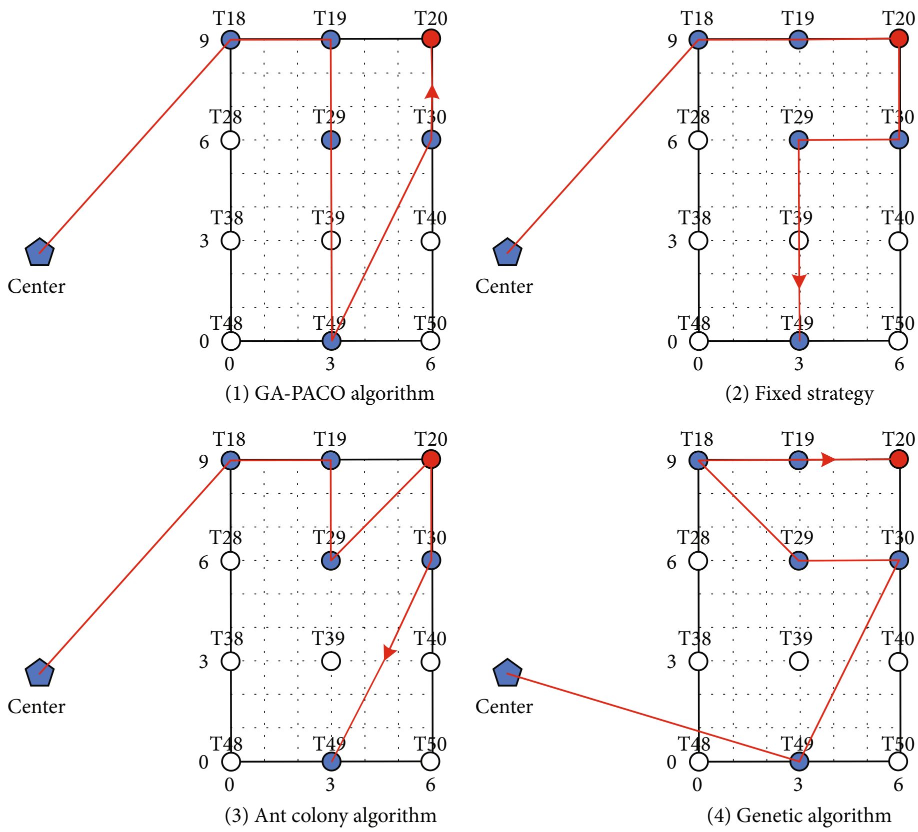

Figure 7: Area 3.

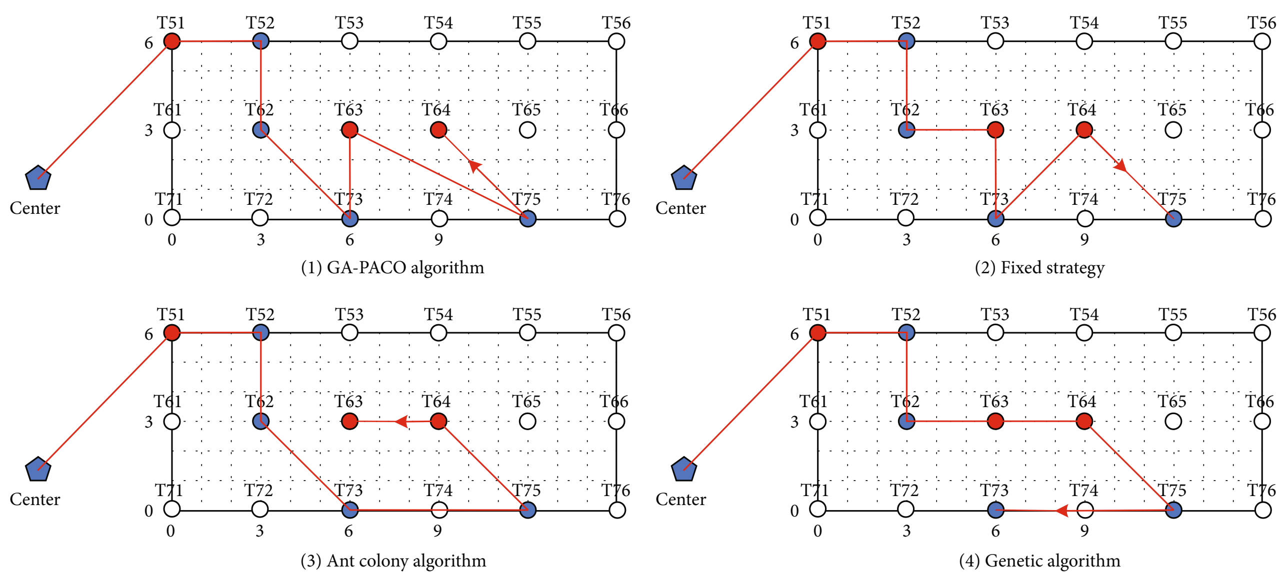

Figure 8: Area 4.

generation of its operation and maintenance path is defined in the following equation:

$$W = \sum_{m=1}^{m} \sum_{i=1}^{n} P_t^i(v(t))[(i-1)(R_{i-1} + \bar{t}_{i-1})], \tag{16}$$

where W represents the total power generation of the wind turbines on the maintenance route; i represents the number of wind turbines that have been repaired; $P_t^i(v(t))$ represents the output power of the ith unit at time t; R_{i-1} represents the travel path time from the i-1th to the ith wind turbine; $\bar{t}_{i-1}$ represents the average maintenance time required for the current turbines; and m indicates the number of zones.

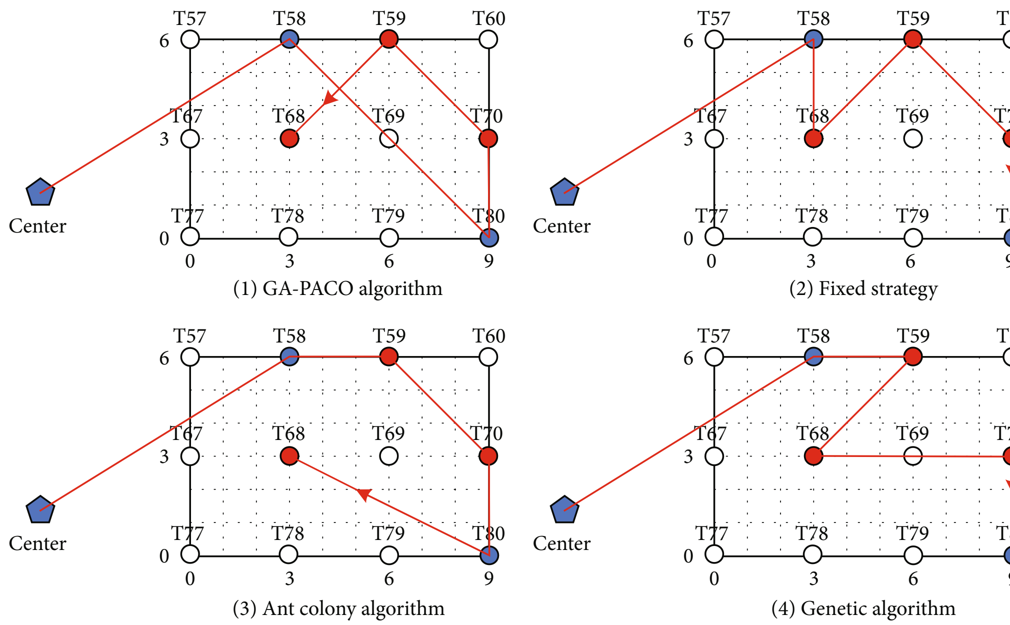

Figure 9: Area 5.

Table 3: Simulation of 80 turbines.

Algorithm	W_p (ten thousand kWh)	W_f (ten thousand kWh)	TEA (%)
GA-PACO algorithm	279,912	278,011	99.32
Fixed strategy	279,912	273,892	97.85
Ant colony algorithm	279,912	276,785	98.88
Genetic algorithm	279,912	274,629	98.11

Table 4: Simulation of 160 turbines.

Algorithm	W_p (ten thousand kWh)	W_f (ten thousand kWh)	TEA (%)
GA-PACO algorithm	559,824	550,081	98.25
Fixed strategy	559,824	541,149	96.66
Ant colony algorithm	559,824	548,515	97.98
Genetic algorithm	559,824	545,920	97.51

4.3. Model Design. The simulation software used for modeling and simulation is AnyLogic [33]. This software places the agents in the port and wind farm environment to establish the connection between the agents. The operation and maintenance simulation system for offshore wind power generation is the result of the interactive behavior of agents such as ships and wind turbines to operate and maintain; at the same time, it also provide the functions of data calculation and visual display, which facilitates the statistics of simulation data.

The simulated offshore wind farm turbine T1 is about approximately 42 km offshore, and the turbine spacing is 3 km. There are 80 2500 W wind turbines installed in the wind farm. The 3D and 2D images of the offshore wind farm show the location and status of the turbines as shown in Figures 2 and 3.

4.4. Cluster Partition. A model of the probability of failure is established according to the statistical data of the faults of the turbines over the years. The failure probability model is established randomly, because the failure probability of each part of the turbine is different, and the probability of failure at any time is simulated according to the exponential distribution. Through the K-means clustering algorithm [34, 35], the characteristics of the turbines are extracted, and the turbines are clustered and partitioned. The turbines are classified according to the rules that most of them are fault maintenance, most of them are replacement of spare parts, and the number of maintenance and maintenance of the two is equal. The initial division of the unit to be repaired is shown in Figure 4.

4.5. Algorithmic Routing Comparison. Counting 80 and 160 two groups of wind turbines, the specific parameters are set as follows: the number of operation and maintenance ship agents is 5 according to the clustering partition, the staff

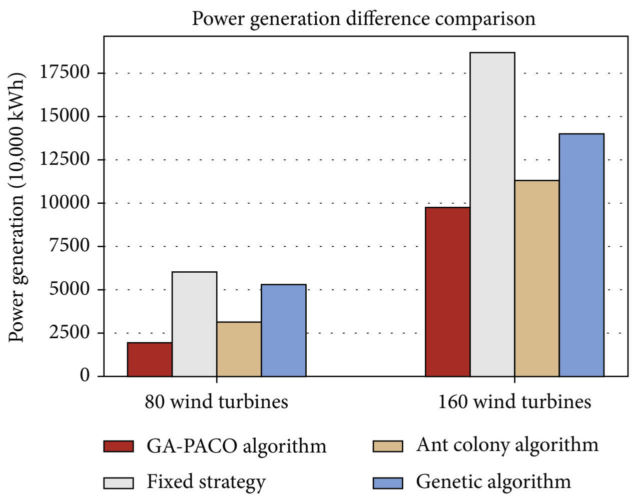

Figure 10: Comparison of the power generation difference.

and spare parts are sufficient, and the average maintenance time of offshore wind turbines is shown in Table 1.

This paper compares the GA-PACO algorithm with the operation and maintenance strategies used in the fixed strategy, traditional ant colony algorithm, and genetic algorithm, as shown in Table 2 and Figures 5–9.

Through the power generation obtained by the path planning in each area, the total power generation of the five regions using different algorithms is calculated, and the total power generation of the GA-PACO algorithm is 349197.5 kWh, and the total power generation of the fixed strategy is 305267.5 kWh, the total power generation of the ant colony algorithm is 335167.5 kWh, and the total power generation of the genetic algorithm is 349197.5 kWh. It can be seen that the total power generation of the GA-PACO algorithm is higher than that of other traditional algorithms.

4.6. Model Algorithm Validation Verification

4.6.1. Research on 80 Turbines. The simulation system calculates 80 wind turbines as shown in Table 3. The specific parameters are set as follows: the number of operation and maintenance ship agents is 5 according to the clustering partition, with sufficient staff and spare parts, and the actual power generation W_f in one year is 2,780.11 million kWh. Within a year, the ideal power generation W_p of 80 wind turbines with a power of 2500 W is 2,799,120,000 kWh. The technical power generation availability rate of the wind farm in one year is defined in the following equation:

$$\mathrm{TEA} = \frac{W_f}{W_p} \times 100\%. \tag{17}$$

4.6.2. Research on 160 turbines. When the scale of the wind turbine is expanded to 160 wind turbines, using the GA-PACO algorithm to simulate the actual power generation, W_f for one year is 5,500,810,000 kWh, and within one year, the ideal power generation W_p of 80 wind turbines with a power of 2,500 W is 5,598,240,000 kWh. Equation (17) obtains the technical power generation availability TEA of each algorithm as shown in Table 4.

According to the difference between the theoretical power generation and the actual power generation, the comparison of the power generation difference between 80 wind turbines and 160 wind turbines using the GA-PACO algorithm and other algorithms is shown in Figure 10.

We compared the power generation of 80 turbines and 160 turbines. When simulating 80 wind turbines, the GA-PACO algorithm has the smallest difference between the power generation and the ideal power generation, and the power generation increases by 12.26 million kWh, and the TEA increases by 0.44%. When simulating 160 wind turbines, the power generation increased by 15.66 million kWh, and the TEA increased by 0.27%. It can be concluded that when the scale of the wind farm increases, the expected convergence time of the GA-PACO algorithm increases; that is, the time complexity increases; the increase in the number of ants in the algorithm reduces the expected convergence time; that is, the time complexity decreases.

5. Conclusion

In view of the failure of offshore wind turbines, this paper proposes a multi-agent-based simulation model for the operation and maintenance path planning of offshore wind farms. By integrating a genetic algorithm and an improved ant colony algorithm and applying it to the field of wind farms, it improves the utilization of maintenance resources and thus enhances power generation efficiency. Firstly, the units to be repaired are clustered and partitioned, and multiple agents are set up for maintenance to improve the power generation efficiency. By integrating the genetic algorithm, the algorithm can improve the efficiency in the early stage of the model and perform a global search. Introducing a heuristic factor and improving the pheromone algorithm strategy can make the algorithm better find the optimal path. Through the simulation experiments, the algorithm in this paper is compared with the fixed strategy traditional ant colony strategy and genetic algorithm, and the algorithm in this paper has stronger search ability. The GA-PACO algorithm proposed in this paper has higher comprehensive performance under multiagent conditions, provides an optimal maintenance strategy, and shows the effectiveness of finding the optimal solution.

Data Availability

Data is available in the following link: https://pan.baidu.com/s/1eFMa41ZHtAnvORcQo8fyNAExtraction code: 5dmn.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was funded by the Science and Technology Department of Hubei Province of China Project Foundation (2021CFB119), Department of Education Youth Talent Fund of Hubei Province of China (Q20211204), Scientific Research Project of Hubei Provincial Department of Education (Q20161201), and Natural Science Research Project of Yichang in Hubei Province (A22-3-009).

References

[1] Z. Zhang, "Multi-ACO application in routing and scheduling optimization of maintenance fleet (RSOMF) based on conditions for offshore wind farms," *Journal of Power and Energy Engineering*, vol. 6, no. 10, pp. 20–40, 2018.

[2] K. Ming, "Solving path planning problem based on ant colony algorithm," in *2017 29th Chinese control and decision conference (CCDC)*, pp. 5391–5395, Chongqing, China, 2017.

[3] S. Yan, "Research on path planning of auv based on improved ant colony algorithm," in *2021 4th International Conference on Artificial Intelligence and Big Data (ICAIBD)*, pp. 121–124, Chengdu, China, 2021.

[4] Q. Dongli, "Research on terminal path selection based on hybrid genetic-ant Colony algorithm," in *2020 international conference on computer engineering and application (ICCEA)*, pp. 353–358, Guangzhou, China, 2020.

[5] Q. Su, W. Yu, and J. Liu, "Mobile robot path planning based on improved ant Colony algorithm," in *2021 Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS).*, pp. 220–224, IEEE, 2021.

[6] I. Fonseca, J. T. Farinha, and F. M. Barbosa, "Maintenance planning in wind farms with allocation of teams using genetic algorithms," *IEEE Latin America Transactions*, vol. 12, no. 6, pp. 1062–1070, 2014.

[7] L. Zhai and S. Feng, "A novel evacuation path planning method based on improved genetic algorithm," *Journal of Intelligent Fuzzy Systems*, vol. 42, pp. 1813–1823, 2022.

[8] J. Wang, X. Shang, T. Guo, J. Zhou, S. Jia, and C. Wang, "Optimal path planning based on hybrid genetic-cuckoo search algorithm," in *2019 6th International Conference on Systems and Informatics (ICSAI)*, pp. 165–169, Shanghai, China, 2019.

[9] F. Pan, "Research on path planning of AUV based on improved genetic algorithms," in *2021 international conference on computer, control and robotics (ICCCR)*, pp. 26–29, Shanghai, China, 2021.

[10] W. Wanliang, C. Haoli, L. Guoqing, L. Longlong, and Z. Yanwei, "Vehicle routing planning for multi-distribution centers based on deep reinforcement learning [J]," *Control and Decision*, 2022.

[11] J. Chun, Y. Zhang, and W. Cong, "Distributed multi-agent ant colony algorithm for vehicle routing problem with time windows [J]," *Computer Application Research*, vol. 35, no. 3, pp. 666–670, 2018.

[12] C. A. Irawan, D. Ouelhadj, D. Jones, M. Stålhane, and I. B. Sperstad, "Optimisation of maintenance routing and scheduling for offshore wind farms," *European Journal of Operational Research*, vol. 256, no. 1, pp. 76–89, 2017.

[13] W. Chi, Z. Ding, J. Wang, G. Chen, and L. Sun, "A generalized Voronoi diagram-based efficient heuristic path planning method for RRTs in mobile robots," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 5, pp. 4926–4937, 2022.

[14] H. M. Chung, S. Maharjan, Y. Zhang, F. Eliassen, and K. Strunz, "Placement and routing optimization for automated inspection with unmanned aerial vehicles: a study in offshore wind farm," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, pp. 3032–3043, 2021.

[15] H. Chunyang, J. Ping, and Z. Genrong, "Application of improved ant colony algorithm in AGV path planning [J]," *Computer Engineering and Applications*, vol. 56, no. 8, pp. 270–278, 2020.

[16] Z. Jing, T. Yunfeng, X. Jiang Guoping, and D. J. Fengyu, "Path planning of mobile robots based on improved ant colony algorithm [J]," *Journal of Nanjing University of Posts and Telecommunications (Natural Science Edition)*, vol. 39, no. 6, pp. 73–78, 2019.

[17] Ł. Kuczkowski and R. Śmierzchalski, "Comparison of single and multi-population evolutionary algorithm for path planning in navigation situation," *Trans Tech Publications Ltd*, vol. 210, pp. 166–177, 2013.

[18] Y. Liu, X. You, and S. Liu, "Multi-ant colony optimization algorithm based on hybrid recommendation mechanism," *Applied Intelligence*, vol. 52, no. 8, pp. 8386–8411, 2022.

[19] Y. Wang and Z. Han, "Ant colony optimization for traveling salesman problem based on parameters optimization," *Applied Soft Computing*, vol. 107, article 107439, 2021.

[20] W. Li, L. Xia, Y. Huang, and S. Mahmoodi, "An ant colony optimization algorithm with adaptive greedy strategy to optimize path problems," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 3, pp. 1557–1571, 2022.

[21] A. Allal, M. Sahnoun, R. Adjoudj, S. M. Benslimane, and M. Mazar, "Multi-agent based simulation-optimization of maintenance routing in offshore wind farms," *Computers & Industrial Engineering*, vol. 157, article 107342, 2021.

[22] S. Zhiyong, W. Caixia, and L. Qionghui, "The key issues of China's offshore wind power development during the "14th Five-Year Plan" [J]," *China Electric Power*, vol. 53, no. 7, pp. 8–17, 2020.

[23] J. Li, P. Li, P. Li, L. Tang, X. Zhang, and Q. Wu, "Self-position awareness based on cascade direct localization over multiple source data," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–9, 2022.

[24] X. Peng, Z. Liu, and D. Jiang, "A review of multiphase energy conversion in wind power generation," *Renewable and Sustainable Energy Reviews*, vol. 147, article 111172, 2021.

[25] M. Stalhane, L. M. Hvattum, and V. Skaar, "Optimization of routing and scheduling of vessels to perform maintenance at offshore wind farms," *Energy Procedia*, vol. 80, pp. 92–99, 2015.

[26] J. J. Nielsen and J. D. Sorensen, "On risk-based operation and maintenance of offshore wind turbine components," *Reliability Engineering & System Safety*, vol. 96, no. 1, pp. 218–229, 2011.

[27] L. Kou, Y. Li, F. Zhang et al., "Review on monitoring, operation and maintenance of smart offshore wind farms," *Sensors*, vol. 22, no. 8, p. 2822, 2022.

[28] P. Papadopoulos, D. Coit, and A. A. Ezzat, "Seizing opportunity: maintenance optimization in offshore wind farms considering accessibility, production, and crew dispatch [J]," arXiv preprint arXiv: 2012.00213, 2020.

[29] F. Zhou, X. Tu, and Q. Wang, "Research on offshore wind power system based on internet of things technology,"

International Journal of Low Carbon Technologies, vol. 17, pp. 645–650, 2022.

[30] M. Neshat, M. M. Nezhad, E. Abbasnejad et al., “A deep learning-based evolutionary model for short-term wind speed forecasting: a case study of the Lillgrund offshore wind farm,” *Energy Conversion and Management*, vol. 236, article 114002, 2021.

[31] F. Theuer, M. F. van Dooren, L. von Bremen, and M. Kühn, “Lidar-based minute-scale offshore wind speed forecasts analysed under different atmospheric conditions,” *Meteorologische Zeitschrift*, vol. 31, no. 1, pp. 13–29, 2022.

[32] W. Zhu, B. Castanier, and B. Bettayeb, “A dynamic programming-based maintenance model of offshore wind turbine considering logistic delay and weather condition,” *Reliability Engineering & System Safety*, vol. 190, article 106512, 2019.

[33] D. Muravev, H. Hu, A. Rakhmangulov, and P. Mishkurov, “Multi-agent optimization of the intermodal terminal main parameters by using AnyLogic simulation platform: case study on the Ningbo-Zhoushan Port,” *International Journal of Information Management*, vol. 57, article 102133, 2021.

[34] A. Sen, M. Pandey, and K. Chakravarty, “Random centroid selection for k-means clustering: a proposed algorithm for improving clustering results,” in *2020 international conference on computer science, engineering and applications (ICCSEA)*, pp. 1–4, Gunupur, India, 2020.

[35] H. Xu, S. Yao, Q. Li, and Z. Ye, “An improved k-means clustering algorithm,” in *2020 IEEE 5th international symposium on smart and wireless systems within the conferences on intelligent data acquisition and advanced computing systems (IDAACS-SWS)*, pp. 1–5, Dortmund, Germany, 2020.